Adversarial Examples in Machine Learning

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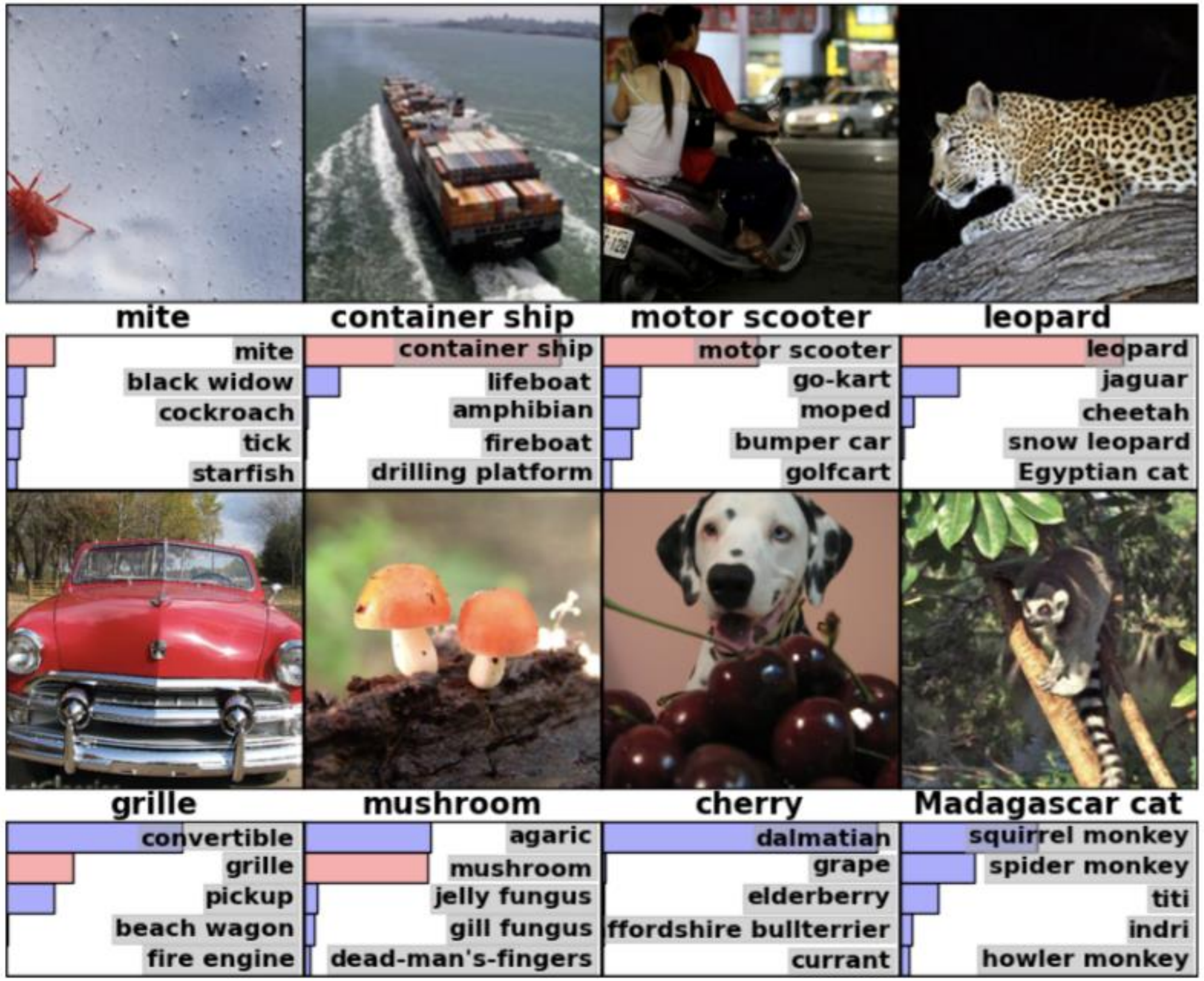
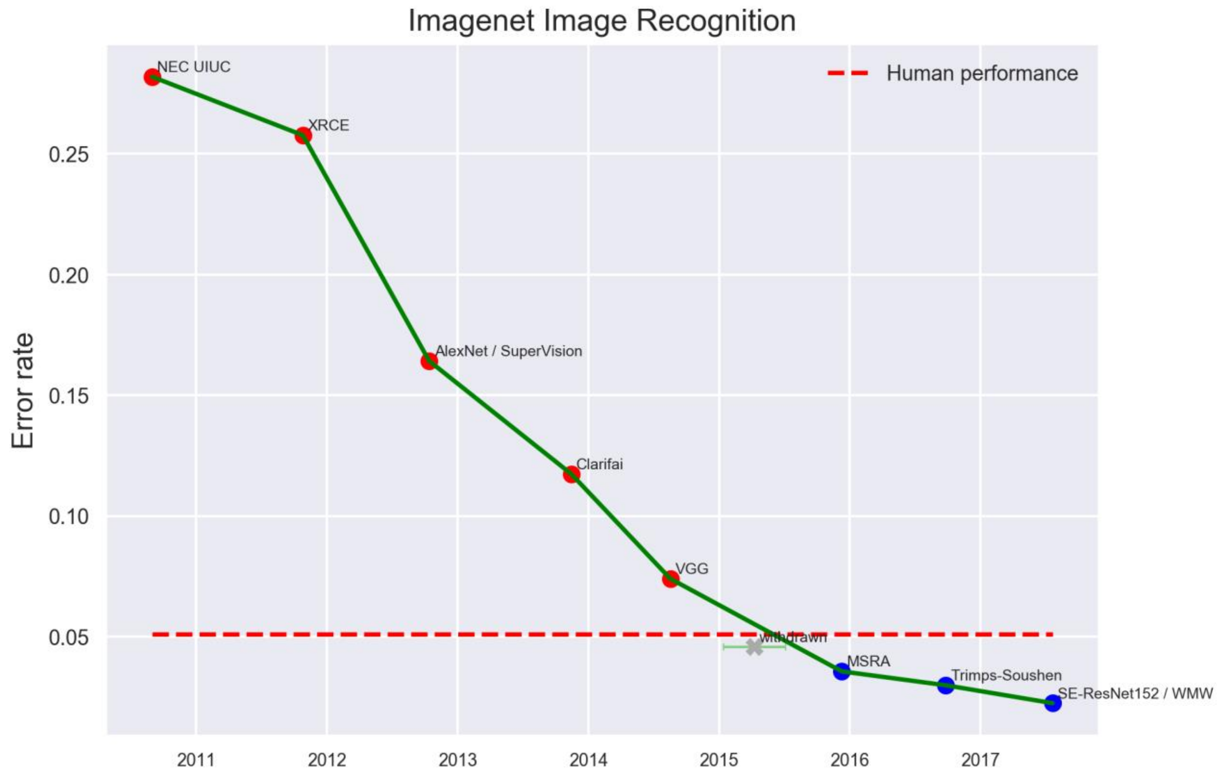
Previously: Image classification

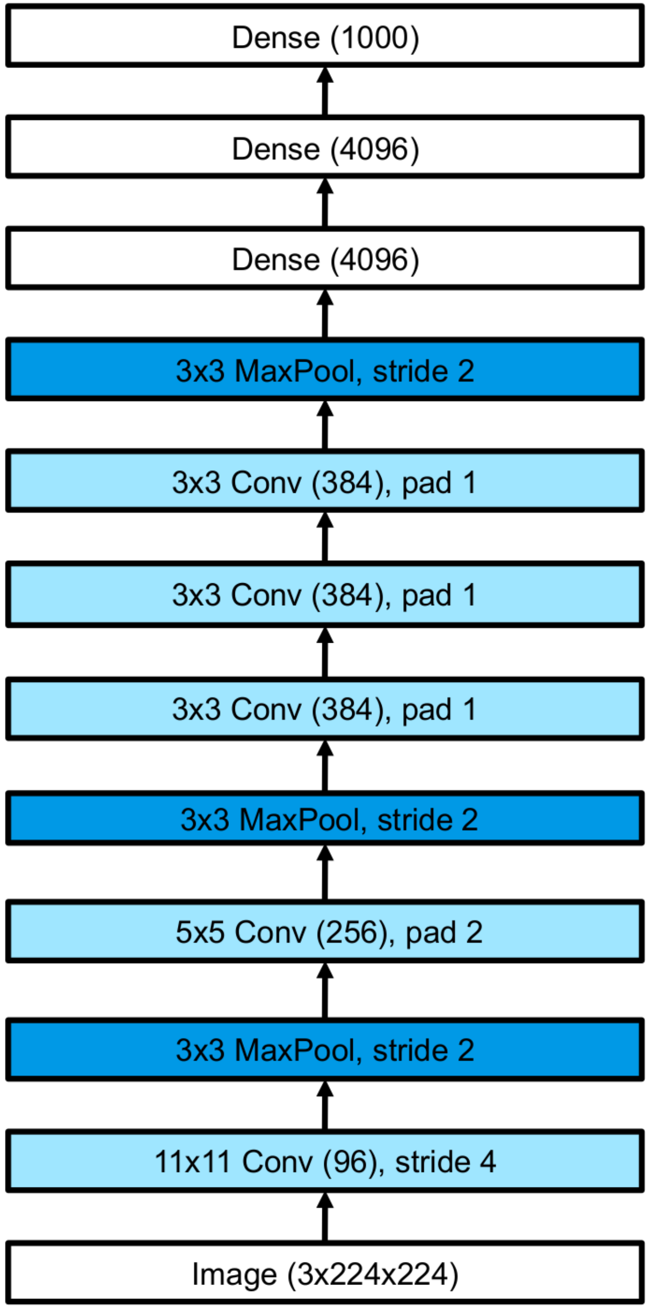


- ImageNet dataset: 14M images, 1000 labels
- **CNNs do very well at these tasks!**

Previously: ImageNet Progress



- 2012: AlexNet wins ImageNet challenge, marks start of deep learning era **(and is a convolutional neural network)**
- 2016: Machine learning surpasses human accuracy



Source: https://www.eff.org/files/AI-progress-metrics.html

Today: A "Reality Check"

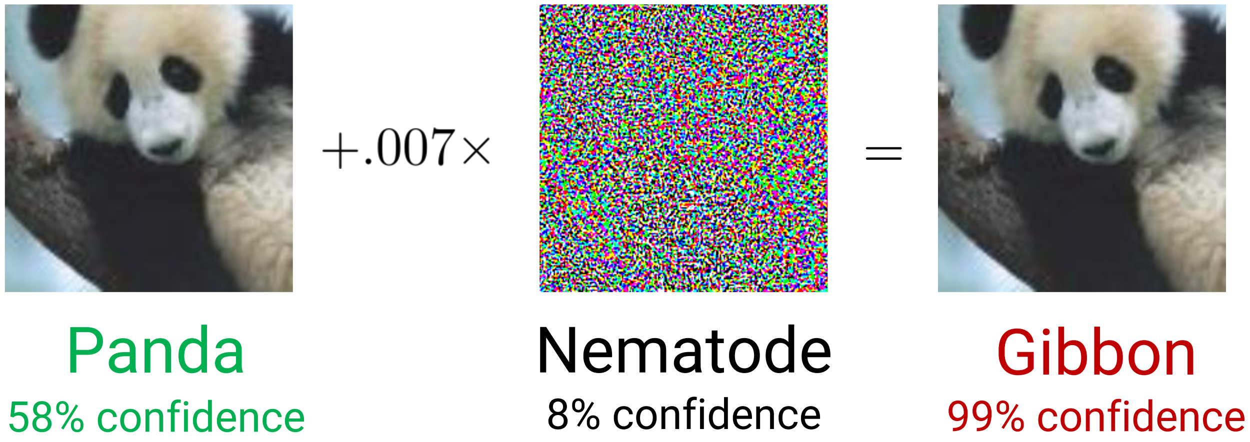
- Do models really "see" images the way humans do?
- Are models learning shortcuts rather than actually solving the task?

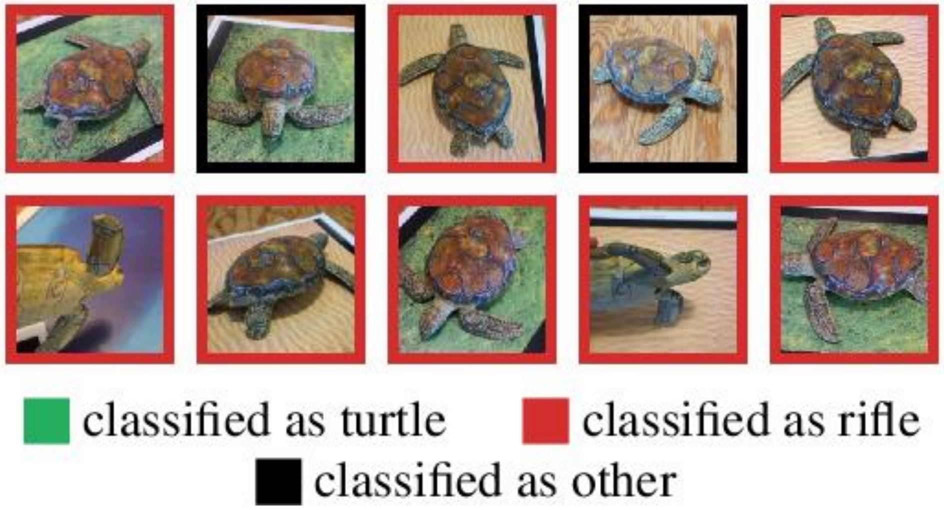
Adversarial Examples

Spurious Correlations

Adversarial Examples

- **Adversarial examples**: Examples crafted by an **adversary** (attacker) to cause a desired behavior by a machine learning model
  - Can exist despite high average accuracy





Goodfellow et al. “Explaining and Harnessing Adversarial Examples.” ICLR 2015.
Sharif et al. “A General Framework for Adversarial Examples with Objectives.” ACM TOPS 2019.
Athalye et al. “Synthesizing Robust Adversarial Examples.” ICML 2019.

Why do we care?

Security

- Fooling facial recognition systems
- Vulnerabilities of safety-critical systems (e.g. self-driving cars)
- Bypassing content moderation or spam detection
- Hacking ranking algorithms (search engine optimization)

Interpretability

- Do models work the way we think they do?
- Understand model weaknesses so we can patch them
- Understand when models might not be reliable

The rules of the game

Defining the **threat model**

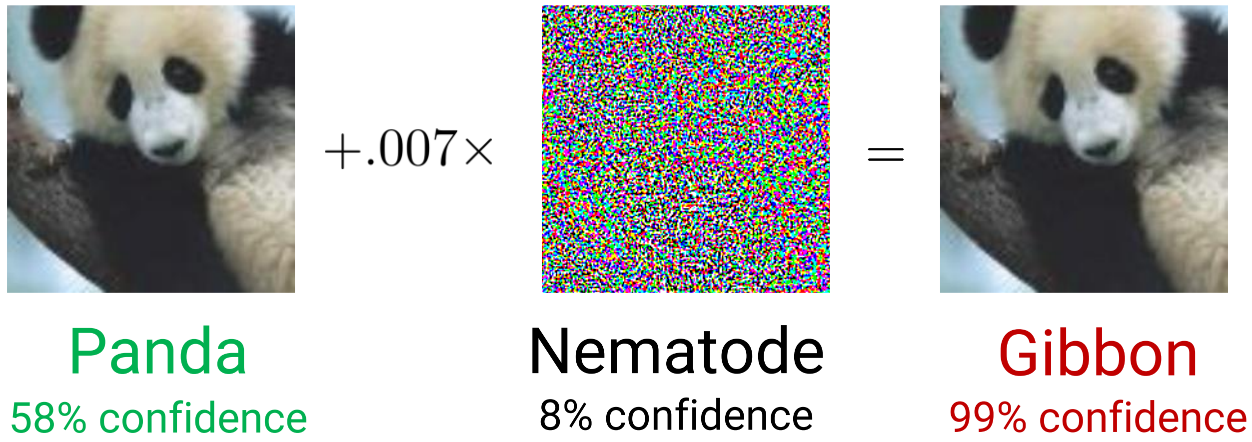
1. **Attack vector**: What can the adversary do?

2. **Adversary’s knowledge**: What does the adversary know?

3. **Adversary’s goal**: What does the adversary want to achieve?

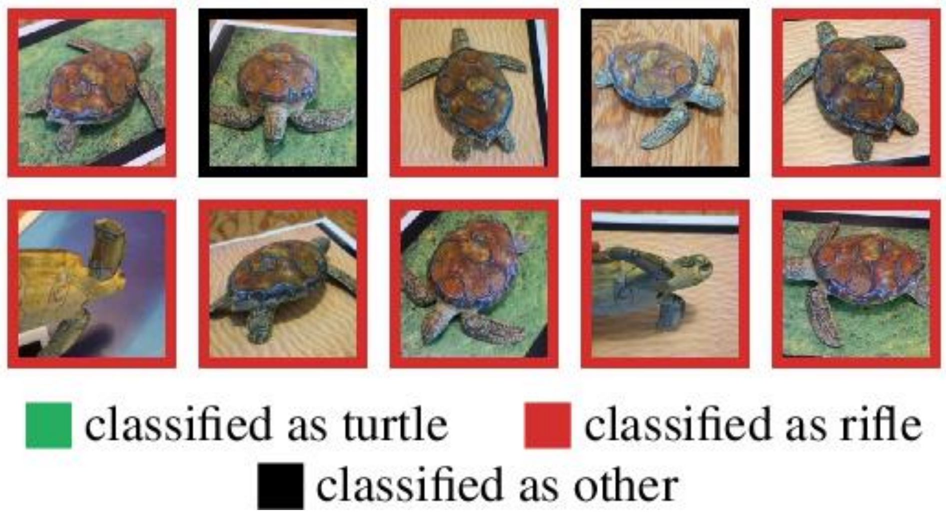
Attack vectors

- Apply a perturbation to input (Constrained attack)



Attack vectors

- Apply a perturbation to input (Constrained attack)
- Completely change the input (Unconstrained attack)
- Add bad training data (Data poisoning)

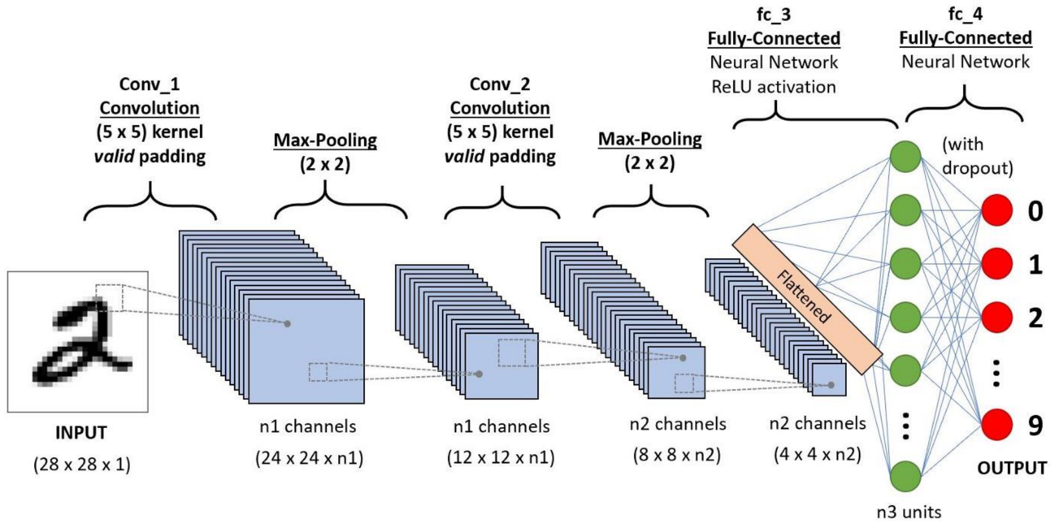


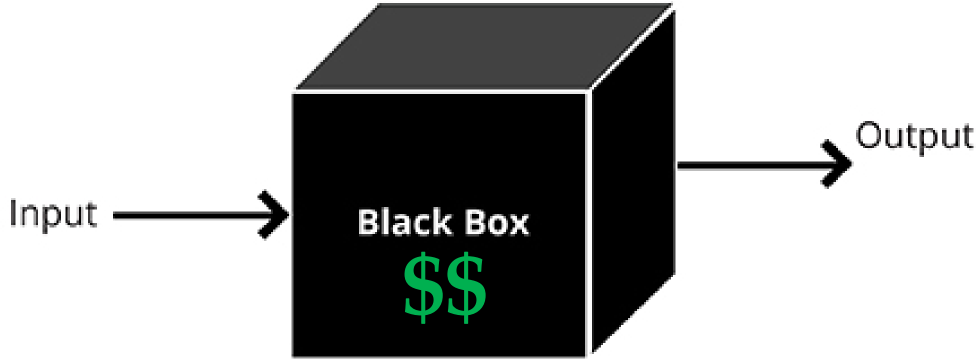
Adversary's knowledge

White-box: Has access to model and all internals (e.g., has model parameters and code)

Black-box: Has access to model only via queries

- May also have a query budget

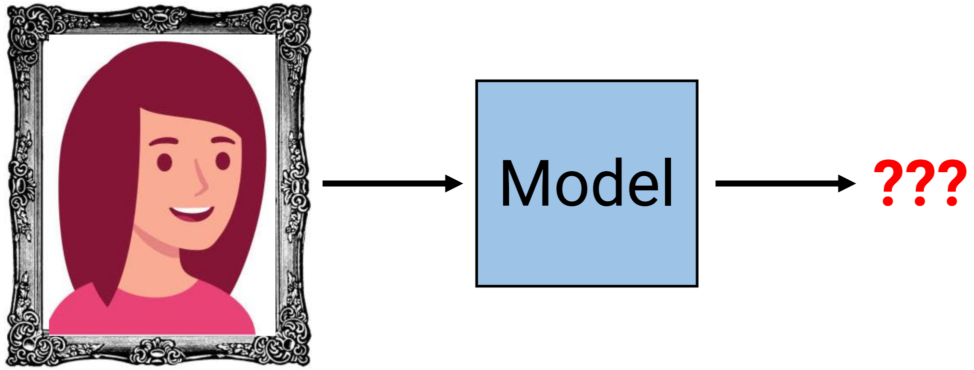




Adversary's goal

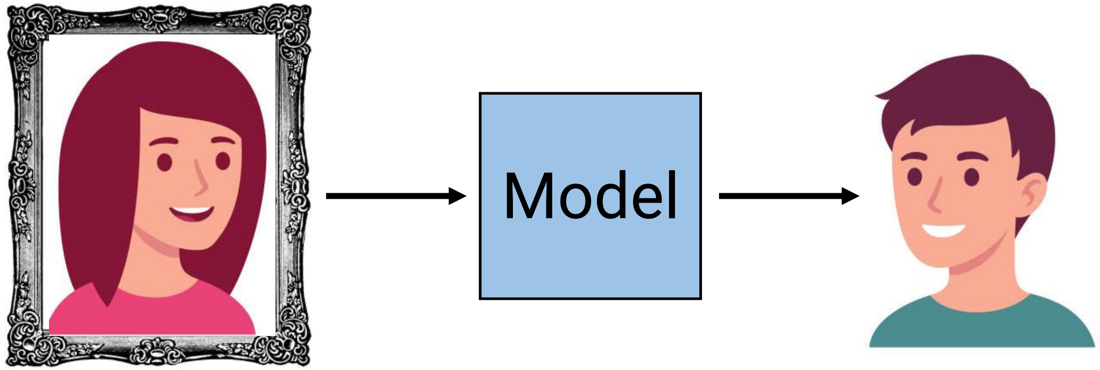
Undirected: Cause any error

- Facial recognition: Avoid being detected as yourself



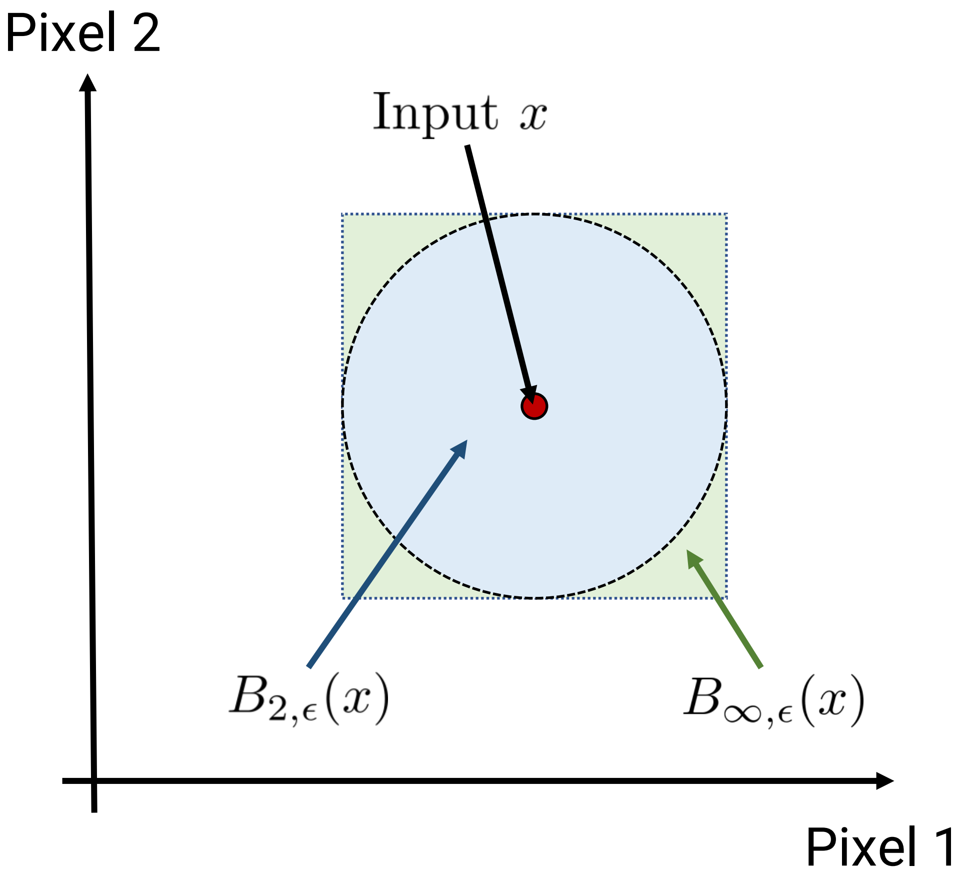
Directed: Cause a specific (wrong) prediction

- Facial recognition: Appear to be some other specific person



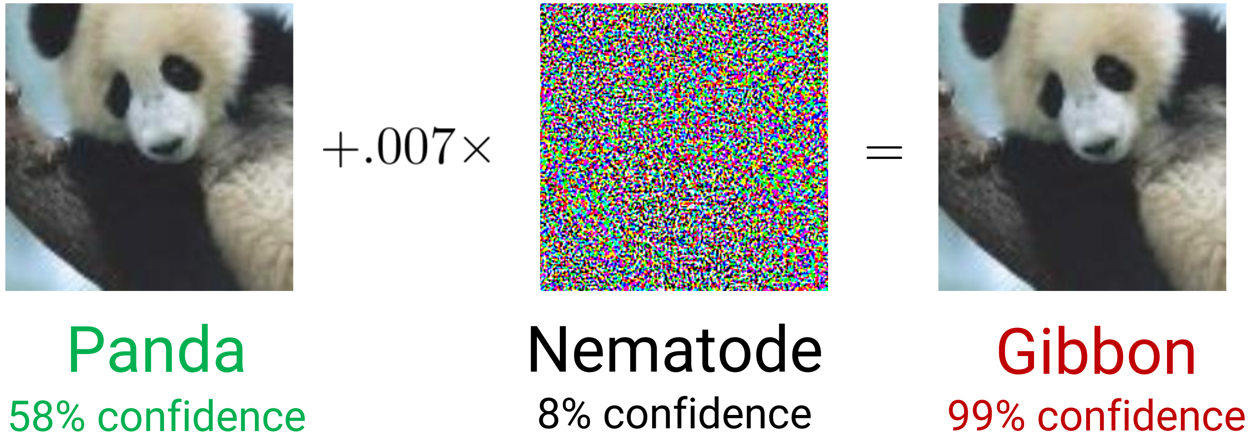
Adversarial perturbations for images

- Informal attack vector: Make imperceptible change to image
- How to formalize?
  - Make new image x' very close to x in pixel space
    - L2 norm: $\|x_i - x\|_2 = \sqrt{\sum_{i=1}^{d}(x'_i - x_i)^2}$
    - L-infinity norm: $\|x_i - x\|_\infty = \max_i |x'_i - x_i|$
  - Constrain norm of difference to be small, e.g. $\|x' - x\|_\infty \leq \epsilon$
    - Equivalently, $x' \in B_{\infty,\epsilon}(x)$
    - Each pixel can change by ϵ



Adversarial perturbations for images

- The rules of the game
  - Attack vector: Given test example x, replace with any $x' \in B_{\infty,\epsilon}(x)$
  - Informally: Attacker can change brightness of each pixel by at most ε
  - Knowledge: White box
  - Goal: Undirected (could also be directed for multi-class)



Attacking a classifier

- Problem statement for attacker
  - Binary classification, model predicts $\text{sign}\left(f(x;\theta)\right)$
  - Given: Image x, label y, model parameters θ
  - Return: $x' \in B_{\infty,\epsilon}(x)$ such that $\text{loss}(x', y; \theta)$ is maximized

Goodfellow et al. “Explaining and Harnessing Adversarial Examples.” ICLR 2015.

Attacking a classifier

- Approximate solution ("Fast Gradient Sign Method" or FGSM)
  - Let $z = x' - x$
  - Idea: Approximate f locally with a linear model

$$f(x';\theta) \approx f(x;\theta) + \boxed{\nabla_x} f(x)^\top (x' - x) = \underbrace{f(x;\theta)}_{\text{Original prediction}} + \underbrace{\boxed{\nabla_x} f(x)^\top z}_{\text{Adversary controls}}$$

Gradient with respect to ***x*** (not the parameters!)

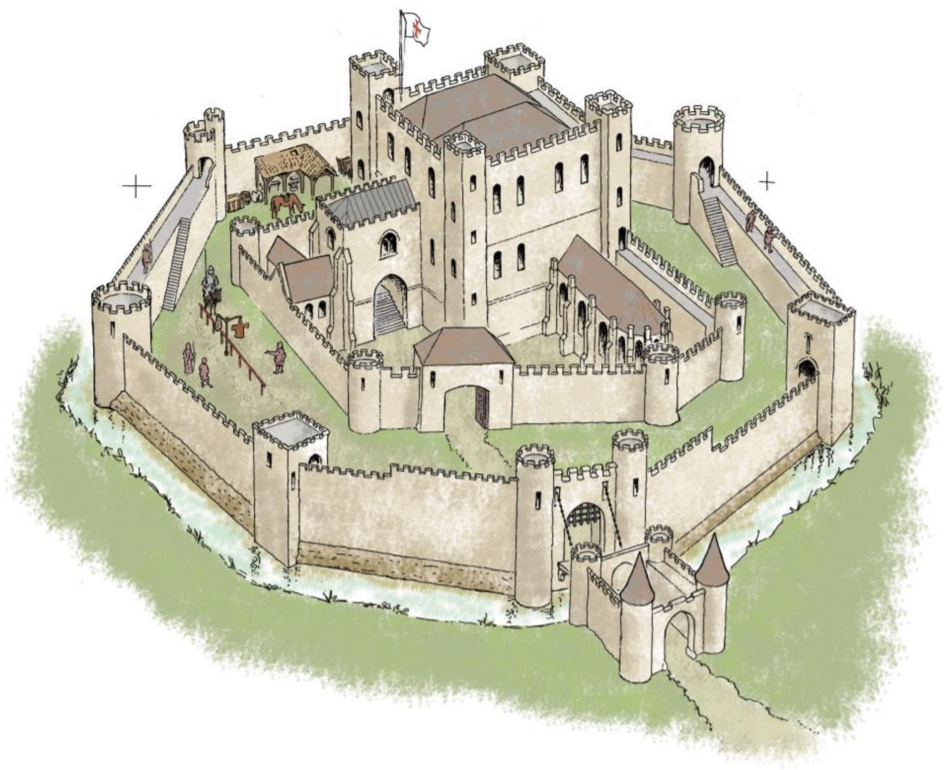
  - To increase *f*, add ε when gradient > 0, subtract ε when gradient < 0
  - Do the reverse if adversary wants to decrease *f*

$\nabla_x f(x)$	1.2	-2.8	0	2.3	
z to **increase** *f(x)*	ε	-ε	0	ε	(Adversary makes model predict y=+1)
z to **decrease** *f(x)*	-ε	ε	0	-ε	(Adversary makes model predict y=-1)

Goodfellow et al. "Explaining and Harnessing Adversarial Examples." ICLR 2015.

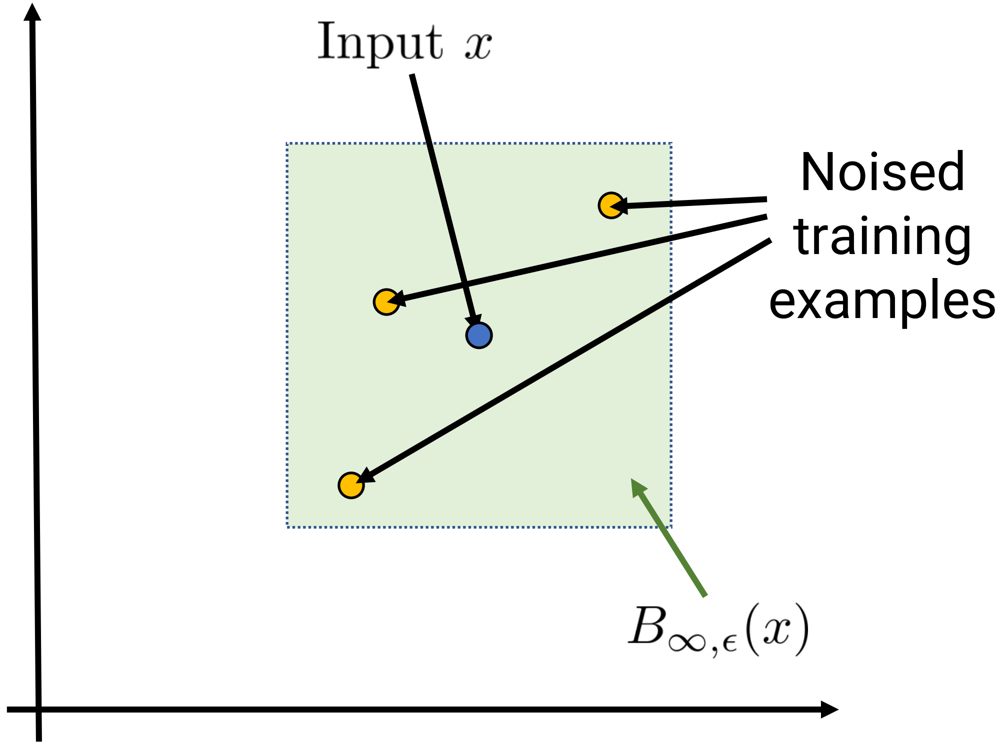
Defending against adversarial perturbations

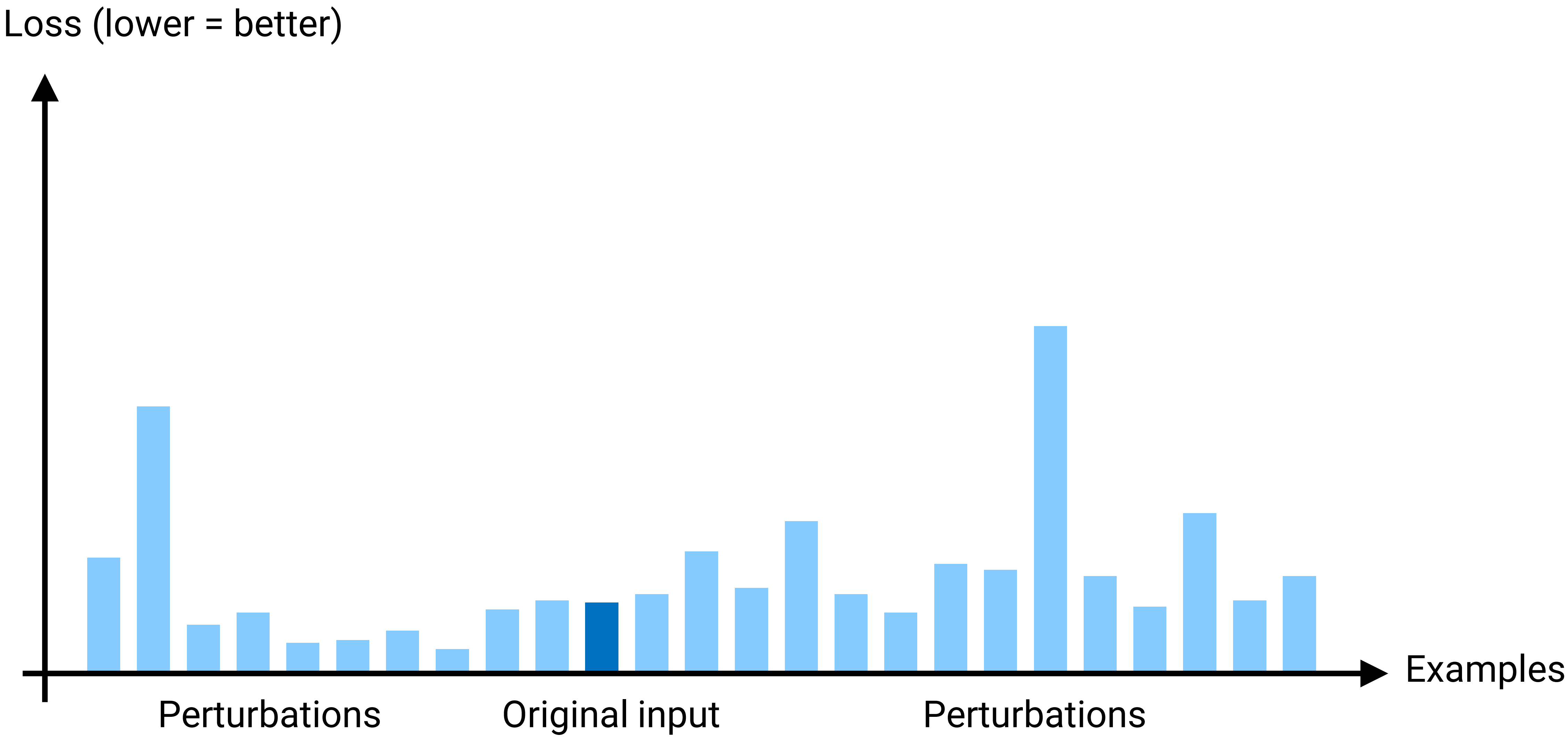
- Problem statement for defender
  - Given: Dataset D and **known threat model**
    - i.e. Assume you know the norm and perturbation radius ϵ
  - Return: Model parameters θ such that attacker cannot succeed
- Adversary has second player advantage!
  - First, you train the model
  - Then the adversary gets to attack it

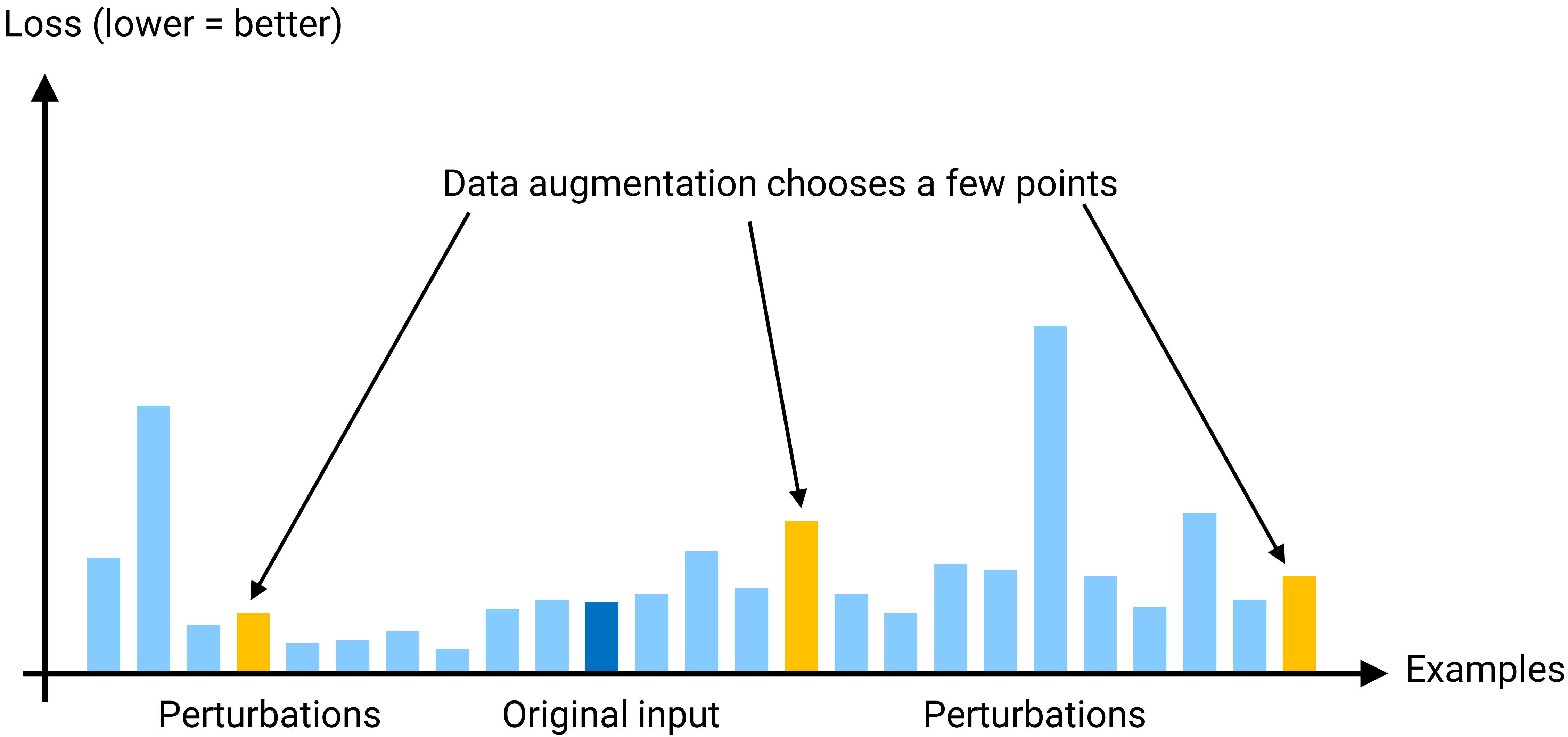


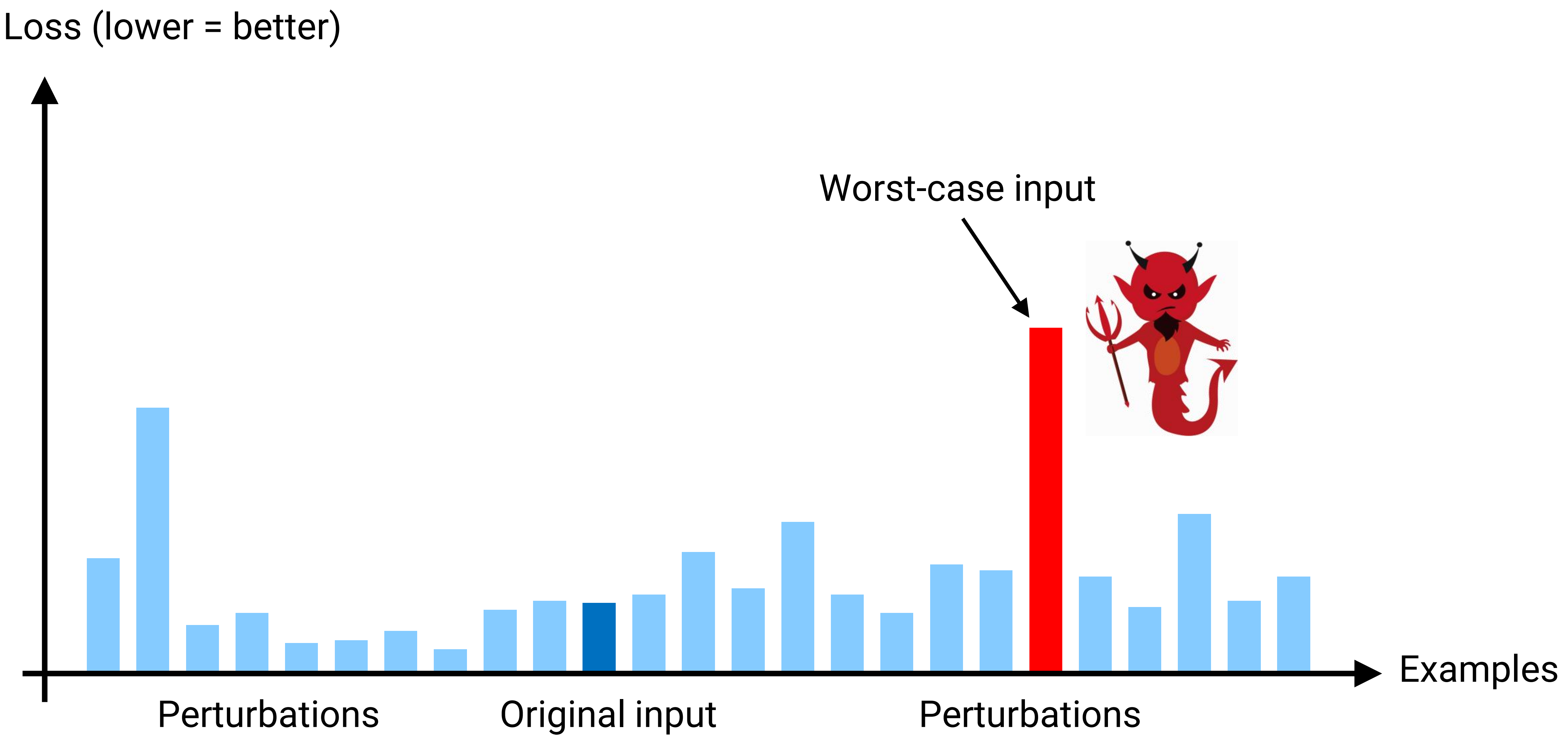
A naïve defense strategy

- **Data augmentation**: Automatically generate additional training examples based on your current data
  - Often a good strategy in general, but not here…
- Random data augmentation
  - Randomly add noise to training examples x within $B_{\infty,\epsilon}(x)$
  - Train on this augmented data
- Problem: Adversary is choosing worst-case perturbation, may be much worse than random perturbation!



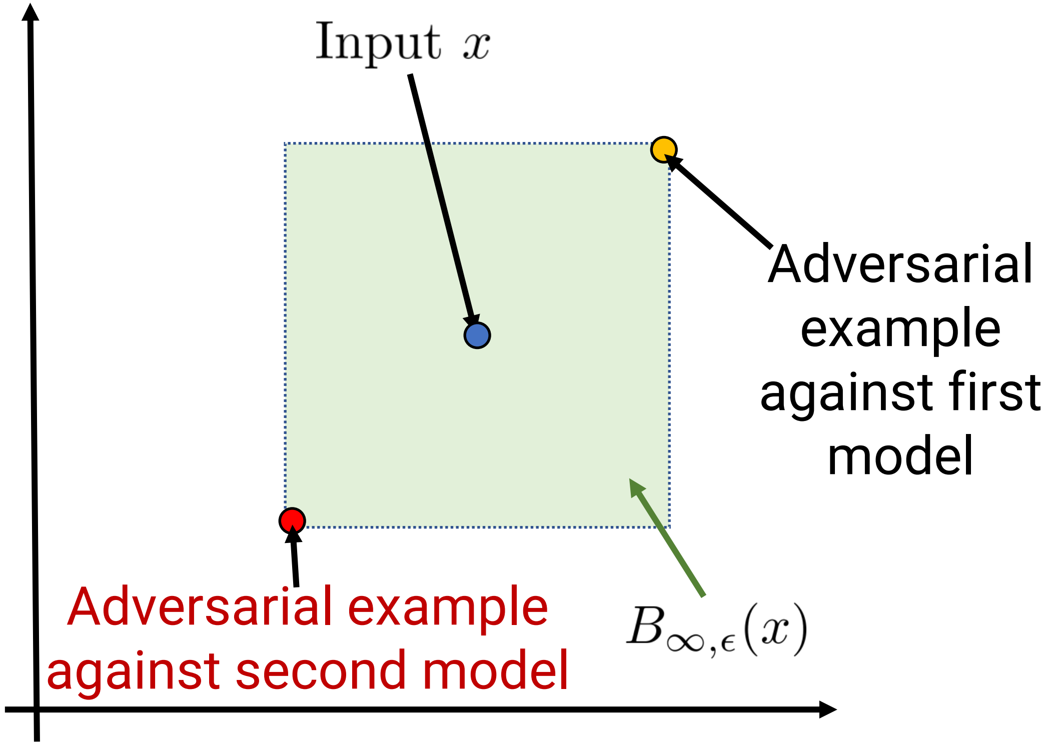

Loss (lower = better)
Examples
Perturbations
Original input
Perturbations


Loss (lower = better)
Data augmentation chooses a few points
Examples
Perturbations
Original input
Perturbations


Loss (lower = better)
Worst-case input
Examples
Perturbations
Original input
Perturbations

Another naïve defense strategy

- “Adversarial data augmentation”
  - Train model normally
  - Generate adversarial examples for this model
  - Add these to training data and retrain
- Flaw: At test time, adversary can perturb in a different way!



Anticipating the adversary

- Normal training loss function: $$\min_{\theta} \sum_{(x,y)\in D} \text{loss}(x, y; \theta)$$

- What we want to optimize instead: $$\min_{\theta} \sum_{(x,y)\in D} \max_{x' \in B_\epsilon(x)} \text{loss}(x', y; \theta)$$

Choose the parameter that minimizes training loss…

On the perturbation that the optimal adversary would choose **against this model!**

Adversarial training

- How can we optimize $\min_{\theta} \sum_{(x,y)\in D} \max_{x' \in B_\epsilon(x)} \ell(y \cdot f(x';\theta))$?

- Run an attack algorithm A (e.g., FGSM) **against current model** to generate $x' = A(x, y; \theta)$
- Plug it in: $\min_{\theta} \sum_{(x,y)\in D} \ell(y \cdot f(\underbrace{A(x,y;\theta)}_{\text{Adversarial example } \textbf{for current model}});\theta))$

- Implementation: Every time you want to do a gradient step, first run the attack, then do gradient step on the adversarial example

Goodfellow et al. "Explaining and Harnessing Adversarial Examples." ICLR 2015.

NLP: Adversarial Unicode attacks

- Images: We could have some **actually imperceptible** perturbations
- Text equivalent: Unicode characters that look like ASCII characters

I. INTRODUCTION

Do x and x look the same to you? They may look identical to humans, but not to most natural-language processing systems. How many characters are in the string “123”? If you guessed 100, you’re correct. The first example contains the Latin character x and the Cyrillic character h, which are typically rendered the same way. The second example contains 97 zero-width non-joiners[1] following the visible characters.

[1]Unicode character U+200C

Boucher et al. “Bad Characters: Imperceptible NLP Attacks.” 2021.

NLP: Typo-based attacks

- Adversarially chosen typos can also cause misclassification
- Think about an RNN or Transformer
  - Input is a set of word vectors
  - Add a typo = completely different word vector for that word!

Alteration	Movie Review	Label
Original	A triumph, relentless and beautiful in its downbeat darkness	+
Swap	A triumph, relentless and beuatiful in its downbeat darkness	–
Drop	A triumph, relentless and beautiful in its dwnbeat darkness	–
+ Defense	A triumph, relentless and beautiful in its downbeat darkness	+
+ Defense	A triumph, relentless and beautiful in its downbeat darkness	+

NLP: Meaning preserving attacks

- Can keep meaning the same (e.g. *“What has”* -> *“What’s”*)
- Security case
  - Alter model prediction while maintaining equivalent meaning to a reader
    - SEO, Plagiarism detection
- Interpretability case
  - Surprising if model succeeds on one input but fails on another that people would think of as equivalent

In the United States especially, several high-profile cases such as Debra LaFave, Pamela Rogers, and Mary Kay Letourneau have caused increased scrutiny on teacher misconduct.

(a) Input Paragraph

Q: What has been the result of this publicity?
A: increased scrutiny on teacher misconduct

(b) Original Question and Answer

Q: What haL been the result of this publicity?
A: teacher misconduct

(c) Adversarial Q & A (Ebrahimi et al., 2018)

Q: What’s been the result of this publicity?
A: teacher misconduct

(d) **Semantically Equivalent Adversary**

Ribeiro et al. “Semantically Equivalent Adversarial Rules for Debugging NLP Models.” ACL 2018.

Summary: Adverarial Examples

- White-box attack strategy (**Fast Gradient Sign Method**)
  - Optimal for linear model (Homework!)
  - Approximate for neural model
- Training-time defense (**Adversarial Training w/ FGSM**)
  - Guards against optimal attack for linear model (Homework!)
  - **Guards against approximate attack for neural model**
- Most famous in images, but can occur in any modality
- Lots of research on more sophisticated attacks/defenses, what this means for deployed models, etc.

Announcements

- Homework 4 released, due Thursday, April 27
  - You should be ready to do everything after today's lecture
- Final Exam
  - Thursday, May 4, 2:00-4:00pm (2 hours)
  - Allowed **two** (double-sided) pages of notes
  - Cumulative exam, somewhat more weight on material after midterm
  - Similar in style to midterm exam
- Last section this Friday
  - Review of course material

Today: A "Reality Check"

- Do models really "see" images the way humans do?
- Are models learning shortcuts rather than actually solving the task?

Adversarial Examples

Spurious Correlations

Previously: Machine learning is a tornado

- …it picks up everything in its path
- Data has all sorts of associations we may not want to model

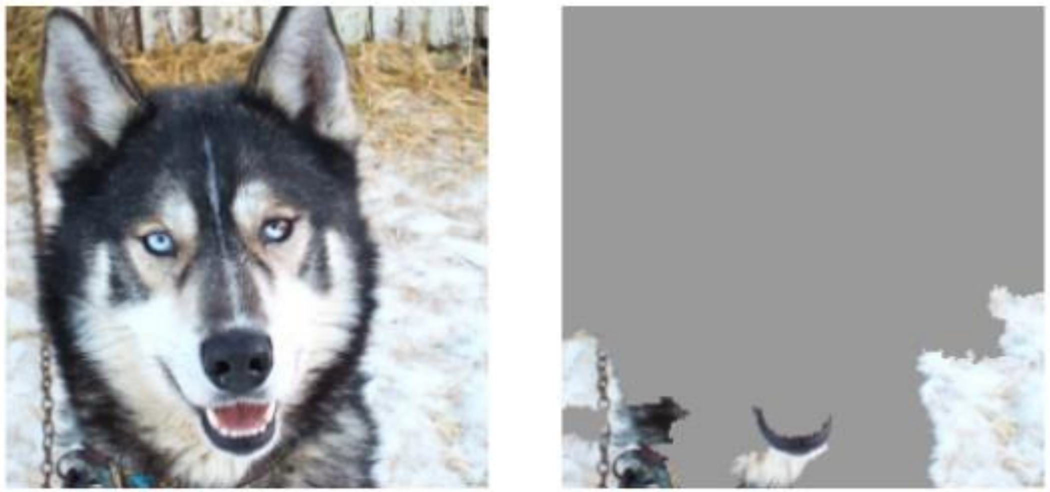
Some pictures of wolves






What do these have in common…?

What does the model learn?



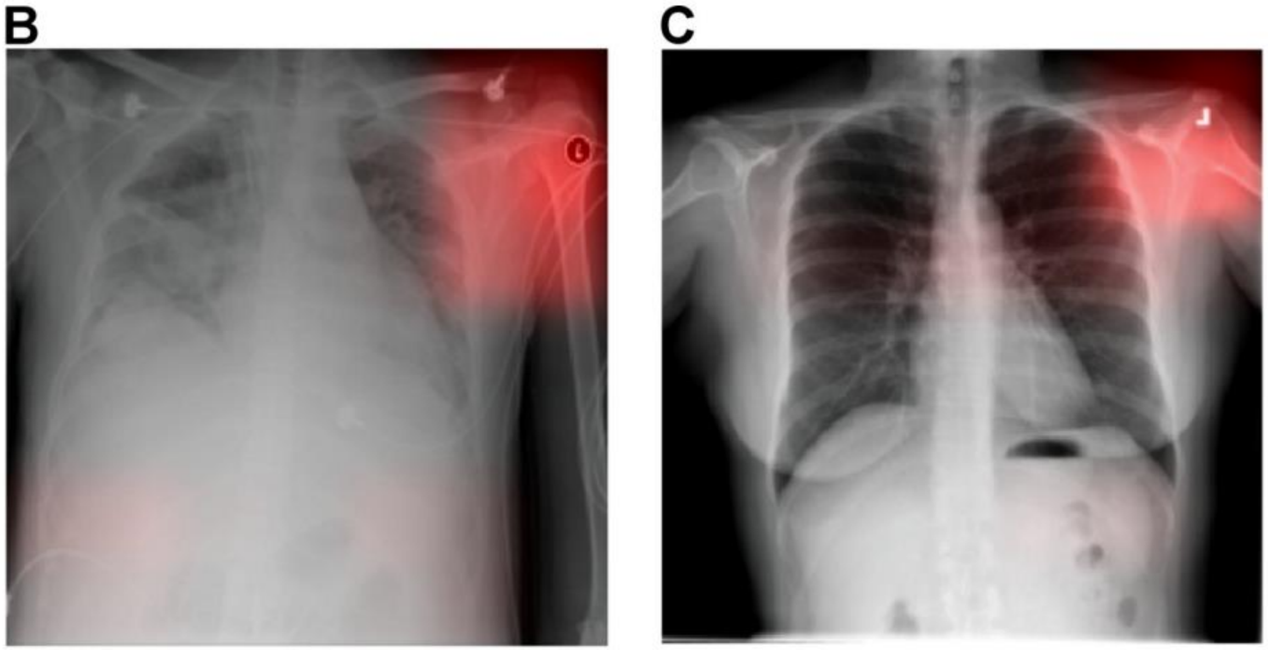
(a) Husky classified as wolf

(b) Explanation

- Model misclassifies husky as a wolf
- Why? Model sees snow and associates it with huskies
- This is a **spurious correlation**
  - Model is just trying to associate input features with label
  - Snow is correlated with “wolf” label, so model learns this
  - But this is ***spurious***—not part of the actual task

https://arxiv.org/pdf/1602.04938.pdf

Spurious correlations in medicine

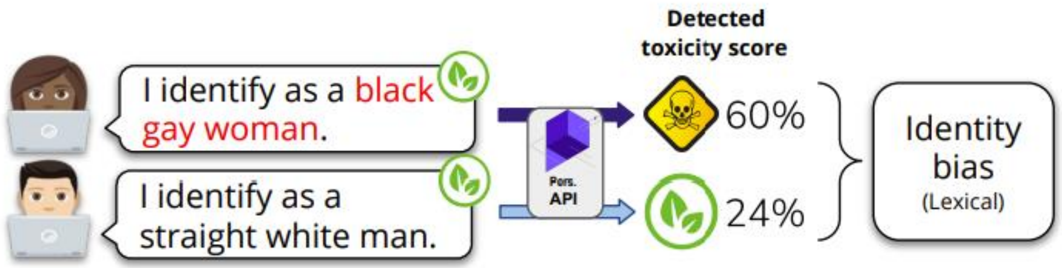


- Task: Detecting pneumonia from chest X-ray
- Spurious correlation: Metallic token radiology technicians place on patient
  - Different hospitals do this differently
  - Different hospitals have different puneumonia prevalence
- Result: Model relies heavily on these hospital-specific tokens!

https://journals.plos.org/plosmedicine/article/file?id=10.1371/journal.pmed.1002683&type=printable

Spurious correlations in NLP

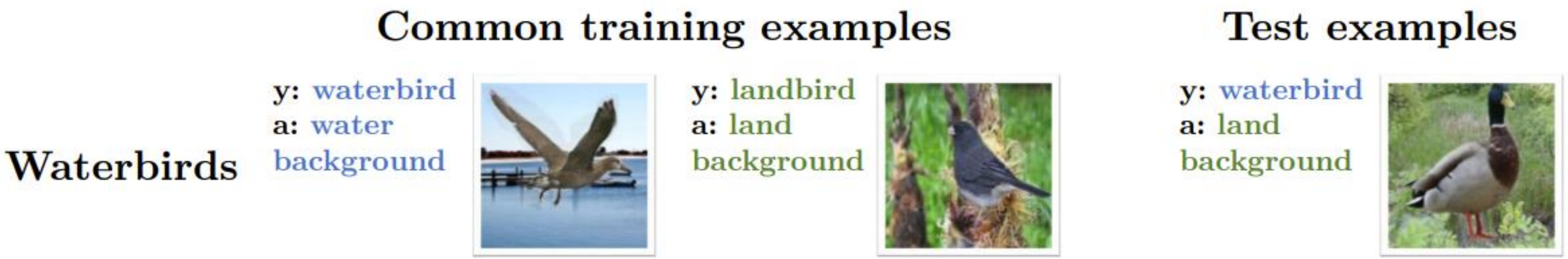
- Hate speech detection: Identity mentions lead to model predicting text as toxic
  - Spurious correlation: Hateful speech directed at specific groups often names those groups
- Sentiment analysis: Some names associated with positive/negative sentiment



Sentence	Toxicity	Sentiment
I hate Justin Timberlake.	0.90	-0.30
I hate Katy Perry.	0.80	-0.10
I hate Taylor Swift.	0.74	-0.40
I hate Rihanna.	0.69	-0.60

https://aclanthology.org/2021.eacl-main.274.pdf
https://aclanthology.org/D19-1578.pdf

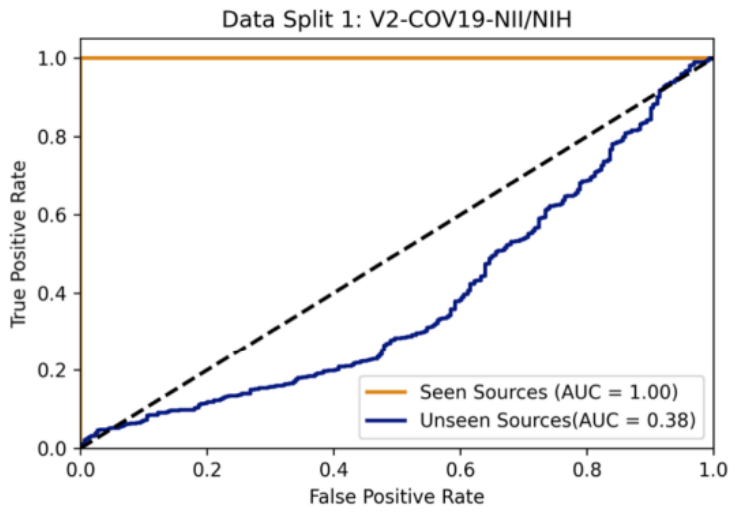
Spurious correlations and generalization

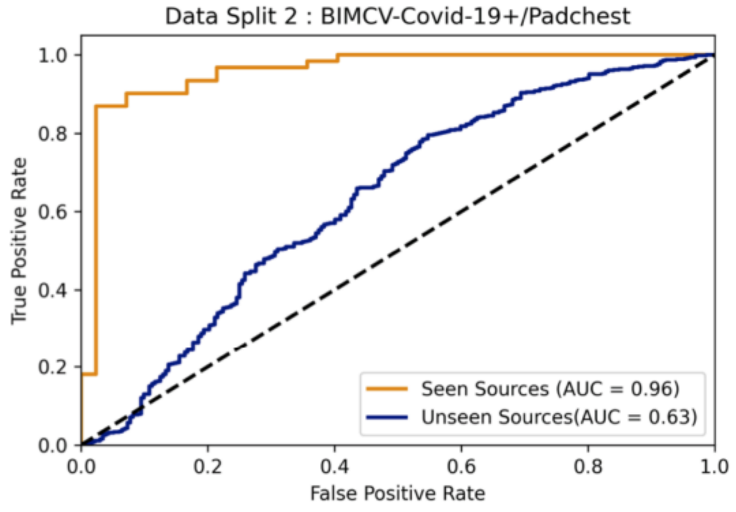


- Task: Identifying bird species
- Spurious correlation: Waterbirds tend to be pictured over water
- Generalization challenge: Cannot identify ducks on land!
  - In general: Overreliance on spurious correlations means your model will perform poorly in scenarios where the correlation no longer holds

https://arxiv.org/pdf/1911.08731.pdf

Spurious correlations and generalization





- Task: Detecting pneumonia from chest X-ray (again) in COVID patients
- Compared two settings
  - Seen sources: Train and test on same data sources
  - Unseen sources: Train and test on different data sources (datasets from 3 different countries)
- Model can be very good on seen sources but worse than random on unseen sources!
  - Likely learns source-specific correlations
  - Similar to HW1 and author identification

Avoiding overreliance on spurious correlation

- Lots of research, but no guaranteed solutions
- Diversifying dataset often helps
- General recommendation: Evaluate **out-of-distribution generalization**
  - Go beyond the hospitals you trained on
  - Find pictures of wolves in atypical backgrounds
- Practice caution: Don’t assume model will generalize without measuring first

Conclusion

- Supervised learning learns patterns from a training dataset
- Things can go very wrong when the test data deviates in some way from the training data
  - Addition of adversarial perturbations
  - New data that breaks spurious correlations in the training data
- Careful evaluation is critical to identify these issues